A Comparison of Spacecraft Attitude Estimation Filters

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1 Abstract

The application of moving horizon estimators (MHE) and particles filters (PF) for spacecraft attitude estimation is investigated. Their performance is compared to the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) through simulations. Due to the nonlinear spacecraft dynamics, the EKF and the UKF are suboptimal. Recently, Moving Horizon Estimators (MHE) and Particle Filters (PF) have been introduced in the process industry and in tracking applications. We show that these new filters can cope better with the nonlinear system dynamics, and result in a higher accuracy.

2 Introduction

For high-performance and high-accuracy spacecraft, the pointing error is dominated by the sensor noise. In order to reduce the effect of sensor noise, the information from different attitude sensors, such as sun sensors, star trackers, inertial measurement units and magnetometers, is combined in an attitude estimation filter. The implementation of this filter in the onboard software requires a low computational cost. In this article, several different filters are implemented, and their performance is compared through simulations. The EKF will serve as the reference filter to which all other filters are compared, as this filter has been the standard attitude filter on spacecraft for many years in the industry.

The spacecraft kinematics and dynamics are described by a nonlinear, discrete-time state-space model. The onboard angular position sensor is corrupted by Gaussian, zero-mean, additive white noise. The angular velocity sensor is corrupted by Gaussian, additive white noise with an unknown bias. This bias vector is appended to the true state vector, to enable joint state and bias estimation.

3 Classical Methods

For linear systems, the Kalman filter is the optimal state observer. The extended Kalman filter was developped for nonlinear systems. The EKF uses a linearization of the system dynamics about its last estimated state. By taking only first-order terms into account, this results in a suboptimal solution. Recently, the unscented Kalman filter was introduced [1]. By making use of the unscented transform, the UKF is able to capture the first and second order terms of the nonlinear system, thereby achieving better estimation performance than the EKF.

4 Moving Horizon Estimation

The state estimation problem can be formulated as an optimization problem, with the estimated states over a finite horizon as optimization variables [2]. By linearizing the system dynamics around the last estimated trajectory, the optimization problem becomes an unconstrained linear quadratic problem, which can be solved efficiently in one step. This algorithm is implemented as a moving horizon estimator. As a further improvement on this basic moving horizon estimator, a second MHE implementation iterates a finite number of times over this reference trajectory. This will lead to only a mild improvement in accuracy, but implies a significant increase in computational cost.

5 Particle Filters

An additionally considered filter is an implementation of a particle filter. This filter will propagate a large number of particles through the spacecraft model, each with artificial random noise added [3]. In order to avoid particle degeneracy, systematic importance resampling is performed at every time step [4]. The *a posteriori* probability density of these particles will approach the real a posteriori probability density for larger numbers of particles, yielding a very accurate filter. Due to the fact that the plant model has to be propagated many times, the computational cost of this filter is high.

References

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